Trust, Risk Barriers and Health Beliefs in Consumer Acceptance of Online Health Services

Completed Research Paper

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Abstract

The Web is an important health information dissemination channel. Potential benefits cannot materialize unless online health information services are accepted and used by consumers. This study develops a research model by integrating the health belief model (HBM) and extended valence framework to explain user acceptance (behavioral intentions). We collected data from a sample of 703 university students in South Africa. Trust had the strongest effect on acceptance. Perceived risk barriers also had significant impacts on acceptance. Furthermore, we confirmed health belief variables, namely perceived susceptibility and severity, are important to consumer acceptance. Self-efficacy was found to moderate the effect of perceived severity on acceptance. The model explains 47.5% of the variance in intentions to use online health information services. Results have helped us identify the relative salience of HBM and extended valence framework in consumer acceptance of online health information services and have important implications for practice.

Keywords: Trust, e-health, risk barriers, health beliefs, perceived susceptibility, perceived severity, online consumer behavior

Introduction

Online health information services have the potential to improve consumer engagement in the self-management of their and their family's health (Harbour and Chowdhury 2007; Song and Zahedi 2007; Yi et al. 2013). Online health information services such as WebMD, Health24 and MedlinePlus offer consumers the promise of a) increased convenience and greater access to information for engaging in self-management of their health, b) reducing uncertainty regarding health status and c) constructing a social and personal sense of health (Cotton and Gaupta 2004; Harbour and Chowdhury 2007; Xiao et al. 2014). They advantage consumers by overcoming the geographic, temporal and cost limitations associated with traditional health information channels (Harbour and Chowdhury 2007; Xiao et al. 2014). They also offer an opportunity for consumers to gain access to different perspectives on health conditions, and to be more informed about and take a more active role in their heath (Rains 2007). However, there are still problems associated with these services that may influence consumer acceptance and usage. For example, one study argues that much of the health-related information found online is inaccurate or misleading to health-information seekers (Abbasi et al. 2012). The trustworthiness and expertise of information providers has often been questioned (Dutta-Bergman 2003; Lemire et al. 2008), and the computer-mediated nature of the services may bring about added anxiety and concerns over the misuse of personal health information (Beldad et al. 2010; Bansal et al. 2010). It is therefore not surprising that consumers may remain hesitant to use online health information services.

If online health information services are going to provide intended benefits then understanding variations in the acceptance and use of these services is a research problem in need of attention. One study suggests that online health information seeking is as important as e-services such as e-shopping for young population (ages 18-34) (Fox 2011), whilst in the context of this study, South Africa, the use of online health services is still emerging relative to other e-services (de Lanerolle 2012). Use of online health information services may however be a special case of e-service acceptance that needs to be understood. This is because usage involves decision making processes for health behaviors that are likely subject to mechanisms other than those associated with typical consumer contexts (Sun et al. 2013) or other task-oriented IS (Kim and Chang 2007). For example, the quality of one's current health, or the risks of becoming ill or exacerbating a condition may be important to predicting acceptance of health information services (Rains 2007). Consequently, consumer engagement with online health services might best be understood as simultaneously a health-related behavior and an e-service usage behavior. Therefore to better understand variations in the use of such services, it is necessary to consider both theories of health behavior, e.g. the Health Belief Model (Rosenstock 1966; Rosenstock 1974), as well as e-service usage behavior, e.g. the extended valence framework (Kim et al. 2009).

The Health Belief Model (HBM) was developed initially in the 1950s by social psychologists to explain preventive health behavior (Rosenstock 1974). The model posits that individual's health behavior depends on the existence of certain beliefs toward a given condition (Chen and Land 1986). There are four health beliefs in this model to explain why people will take an action to prevent or to control illness conditions, namely perceived susceptibility, perceived severity, perceived benefits and perceived barriers. However, past HBM studies have mostly focused on explaining traditional health management behaviors such as smoking cessation, exercise habits and prevention of skin cancer. There are few studies that apply HBM in the context of online health information seeking.

The use of online health information services also requires a consumer to be willing to engage with the information provider through the platforms and technologies of an e-service. The use of e-services across contexts as varied as e-shopping (Jarvenpaa et al. 2000; Corbitt et al. 2003; Gefen et al. 2003; Pavlou 2003; Teo and Liu 2007; Kim et al. 2008), e-banking (Yousafzai et al. 2009; Luo et al. 2010), online legal services (Cho 2006), mobile payment services (Lu et al. 2011; Chandra et al. 2010), e-government (Horst et al. 2007; Bélanger and Carter 2008) and including online health care services (Egea and Gonzalez 2011; Zahedi and Song 2008), have been shown to be influenced by consumer trust and risk beliefs, alongside their perceptions of e-service usefulness. It is argued that because of the technology mediated nature of e-service and the temporal and physical distance between consumers and online providers, both uncertainty and fears of opportunism are inherent in the use of e-services. This uncertainty results in increased consumer risk perceptions and creates a greater need for trust (Pavlou 2003). A recent meta-analysis confirmed trust and risk as important to consumer online behaviors across a number of e-service contexts (Mou and Cohen 2013). In addition, e-service researchers have shown that consumer perceptions of usefulness or benefits are important to acceptance in both commercial (e.g., Gefen et al. 2003; Pavlou 2003; Chandra et al. 2010) and non-commercial contexts (e.g., Wu and Chen 2005). We expect therefore that these concepts of trust, risk and benefit, which have been combined by Kim et al. (2009) into an extended valence framework, will also be relevant to consumer acceptance in the online health context. While trust, risk and benefits have been separately considered in the online health information context (e.g., Lanseng and Andreassen 2007; Bansal et al. 2010; Anderson and Agarwal 2011; Yi et al. 2013; Xiao et al. 2014), they have not been considered together, and have not been integrated with the HBM in an effort to explain consumer engagement with online health information services.

Therefore, the purpose of this study is to develop and test an integrated HBM and extended valence model of consumer acceptance of online health information services. We test the model using data collected from a sample of undergraduate students using an experimental scenarios approach combined with a questionnaire survey.

This paper proceeds as follows: In the next section, the theoretical foundation, the proposed research model and hypotheses are developed. Next, the research methodology is outlined. Thereafter, the empirical results are presented followed by discussion and implications.

Theoretical Foundation and Hypotheses

The health belief model (HBM) was developed by social psychologists to explain health-related behaviors in social psychology and health science (Rosenstock 1966, 1974; Janz and Becker 1984). The basic postulate of this model states that a person's intentions to perform health-related behaviors are determined by perceived threats and outcome expectancies. Perceived threats include the perceived susceptibility of the individual to a health-related threat and perceived severity of the consequences should the threat materialize. Outcome expectancies include the perceived benefits of performing the health-related behavior relative to the perceived barriers associated with performing the behavior. Self-efficacy to perform the behavior has also been added to the HBM in more recent studies (Rosenstock et al. 1988). The HBM is outlined in Figure 1. Health belief model has become one of the most comprehensive models to understand health-related behaviors and to understand why people will take/not take an action to prevent or to control illness conditions (Harrison et al. 1992; Carpenter 2010). This study is focused on information seeking behavior, and not on subsequent actions that may be taken based on the information. HBM is relevant to explanations of behavioral intention toward health information seeking in both online (McKinley and Ruppel 2014) and off-line contexts (Kim et al. 2012).

The valence framework is developed from economics and psychology literature to understand consumer behaviors (Kim et al. 2009). It is based on the view that perceived risk and perceived benefit are two fundamental aspects on consumer purchasing behavior (Peter and Tarpey, 1975). This is because, on the one hand, consumers want to minimize unexpected negative effects whilst, on the other hand, consumers also want to maximize positive effects of purchasing (Kim et al. 2009). In the context of online consumer behaviors, Kim et al. (2009) extended the basic valence framework by adding consumer trust beliefs (see Figure 2). This extend valence framework contends that trust beliefs precede risk perceptions and perceived benefits and that all three subsequently predict online consumer behavior. The valence framework is depicted in Figure 2.

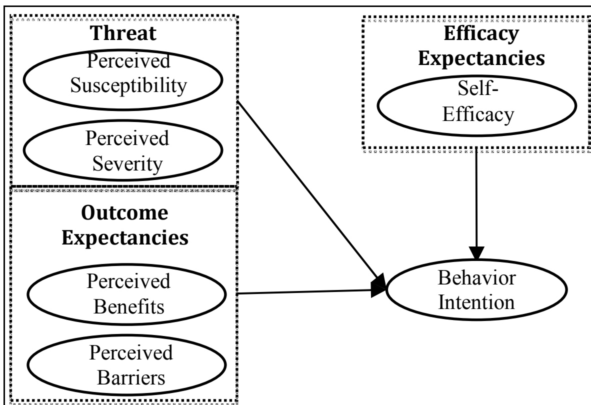

Figure 1. Health Belief Model (Adapted from McKinley and Ruppel 2014)

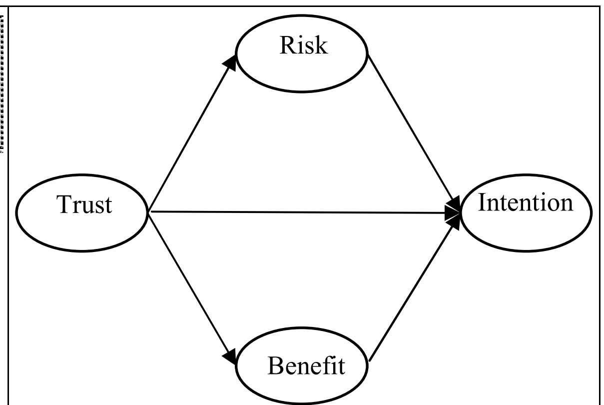

Figure 2. Extended Valence Framework (Kim et al. 2009)

Given both theories are focused on explaining individual's behavioral intentions prior to actual behavior, we are able to consider their integration. Therefore, we integrated the basic HBM and extended valence models to derive our research model (Figure 3). Our dependent variable, representing consumer acceptance, is the consumer's behavioral intention to use online health information services. Because we identify this behavior as simultaneously a health behavior and e-service usage behavior, the model draws on the HBM to identify perceived susceptibility, perceived severity, perceived benefits, perceived barriers and self-efficacy as determinants of intention. Moreover, we draw on the extended valence framework to include trust and its effects on both perceived benefits as well as perceived barriers (in the form of risk perceptions). Because risk perceptions are considered amongst the most significant barriers to consumer online behaviors (Kim et al. 2008), we identify three risks as barriers to intention. These are performance risk, psychological risk and time risk. Consistent with the extended valence framework, both perceived benefits and perceived risks are influenced by consumer trust. Given concerns over the credibility of online information providers (Dutta-Bergman 2003; Lemire et al. 2008), we identify consumer trust in the online health information provider's ability, benevolence, and integrity as relevant trust beliefs with the potential to influence perceived risks, benefits and intentions towards online health services. Finally, our model reflects that self-efficacy may interact with severity and susceptibility to predict health behavior (Carpenter 2010; McKinley and Ruppel 2014). We outline the variables and develop the model's hypotheses in more detail next.

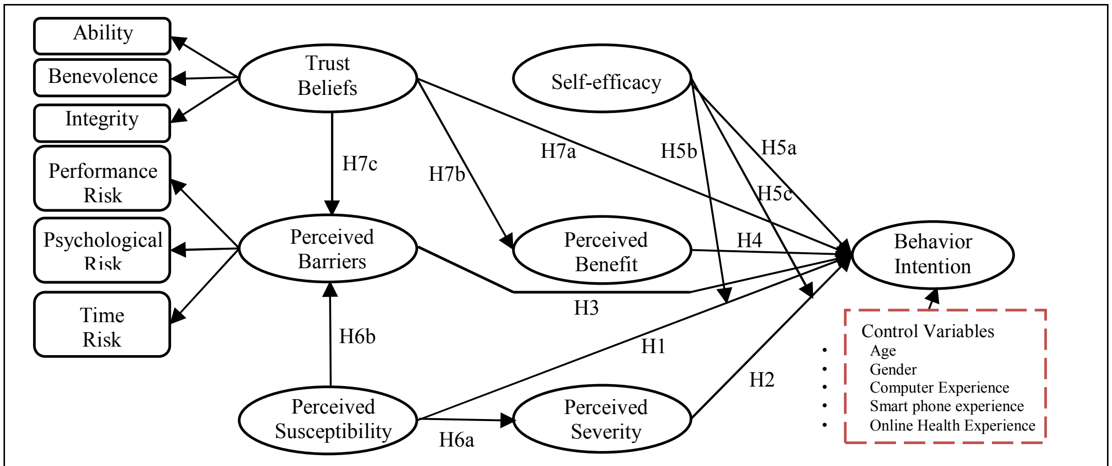

Figure 3. Research Model

Perceived susceptibility is defined as one's feeling of vulnerability to a condition or one's risk perceptions of contracting a condition (Janz and Becker's 1984). The HBM states that health behavior depends on the degree to which an individual believes they are vulnerable such that when an individual's vulnerability or perceived susceptibility is high, they are more likely to do something to prevent the health threat from happening. Therefore, increased levels of susceptibility to one or more health threats are likely to increase consumer intentions to adopt online health services. Past empirical studies across a number of health behaviors empirically support this link (e.g., Marlow et al. 2009). Hence, we hypothesize:

H1: Perceived susceptibility has a positive effect on consumer behavioral intentions toward online health information services.

Perceived severity relates to the seriousness of the clinical or social consequences of the health condition (Janz and Becker 1984). The HBM predicts that if people believe the consequences will be serious, they are more likely to act to avoid the negative health outcome (Rosenstock 1966). When online health information seekers consider that they are likely to suffer seriously as a consequence of not taking action to avoid a health-related threat, they are more likely to consider adopting online health services as part of their self-management and health seeking behaviors (Sun et al. 2013). Previous health behavior studies support this link (e.g., Kim et al. 2012). We therefore hypothesize:

H2: Perceived severity has a positive effect on consumer behavioral intentions toward online health information services.

Risks represent both a barrier to undertaking a health action as well as to engaging in the use of an e-service. Risk in the online context is multi-dimensional (Lim 2003; Featherman and Pavlou 2003) with psychological risk, performance risk and time risk likely to be particularly relevant in the online health context. Psychological risk refers to the possibility that an individual suffers mental stress or loses self-esteem because of the use of online health services (Liao et al. 2010) (e.g., use of the service may give the health information seeker a feeling of unwanted anxiety). Performance risk is the loss incurred if the online service does not meet the consumer's expectation (Sun 2014) (e.g., the consumer may obtain health information that is inaccurate or lacks the expected comprehensiveness). Time risk is the possibility that individuals lose time researching health conditions (Featherman and Pavlou 2003) (e.g., the consumer may waste too much time obtaining the information). The extended valence theory suggests that consumers are motivated to minimize such risks by avoiding behaviors where such risks are considered high. These risks thus present a barrier to acceptance, and according to HBM when individuals perceive strong barriers to taking health actions, they are less likely to engage in the behavior (Carpenter 2010). This leads to the following hypothesis:

H3: Perceived risks are a barrier that will have a negative effect on consumer behavioral intentions toward online health information services.

Within the HBM, perceived benefits are defined as the "beliefs regarding the effectiveness of the various actions available in reducing the disease threat" (Janz and Becker's 1984). The HBM contends that if individuals believe that the perceived benefits from taking preventive a health action is greater than the barriers or risk perceptions then the individual is more likely to perform the behavior (Kim et al. 2012). This is because individuals must believe the action will be effective and must associate it with the likelihood of preventing a health outcome. This is necessary to overcome conflicting motives of avoidance and the possibility of any undesirable consequences that may result from performing the health action (Rosenstock 1974). Thus consumers are likely to adopt online health information when they believe this behavior will prevent a negative health condition or help them maintain or improve their health condition. Benefits are also a core belief within the e-service valence framework where benefits are seen to encourage utility maximizing consumers to make use of online services (Kim et al. 2009). The use of online services can make it more convenient for consumers and empower them and improve their ability to self-manage their health. Past empirical studies support the effects of perceived benefits on online health service adoption (e.g. Lanseng and Andreassen 2007). We therefore hypothesize:

H4: Perceived benefit has a positive effect on consumer behavioral intentions toward online health information services.

Self-efficacy is defined as "the conviction that one can successfully execute the behavior required to produce the outcomes" (Bandura, 1997). It is another predictor in the HBM that can influence health-related behaviors. Normally, people do not try to do something new, unless they think they have the ability to do it. More specifically, in the online health service context, a consumer's Internet self-efficacy is likely to be important to their online activity. If users are confident in their ability to use Internet, they will be more likely to adopt online health information services and perform online health information searching. Past studies have found self-efficacy to exert a strong influence on online health acceptance (Sun et al. 2013; Lim et al. 2011).

H5a: Internet self-efficacy has a positive effect on consumer behavioral intentions toward online health information services.

The effects of susceptibility and severity on user's health behavior may also be moderated by self-efficacy (Carpenter 2010; McKinley and Ruppel 2014). Despite the perceptions of a health threat (i.e., high susceptibility and high severity), individuals who lack self-efficacy to engage with online health providers may view their services as less valuable (McKinley and Ruppel 2014). Individuals lacking in self-efficacy may feel it beyond their control to search out health information and thus perceive use of online health sites for self-management as less appropriate (Rimal 2001). Self-efficacy thus enhances the effects of perceived health threats on behavior such that the effects of severity and susceptibility on intention are likely to be stronger for individuals with higher levels of self-efficacy. Hence, we hypothesize:

H5b: Internet self-efficacy moderates the effect of perceived susceptibility on consumer behavioral intentions toward online health information services.

H5c: Internet self-efficacy moderates the effect of perceived severity on consumer behavioral intentions toward online health information services.

Previous meta-analysis of HBM revealed that severity is the more proximal predictor of behavior for both prevention and treatment related actions (Carpenter 2010). Susceptibility, which is the subjective vulnerability of contracting a condition (Rosenstock 1974) is unlikely to influence behavior unless the individual judges the condition as serious or severe. Consequently, severity may intervene in the relationship between susceptibility and behavior. Others have considered this intervening relationship (Milne et al. 2000). Thus:

H6a: Perceived severity may intervene in the effects of perceived susceptibility on consumer behavioral intentions toward online health information services.

Moreover, the greater an individual's susceptibility to a condition, the more barriers or risks the individual may perceive in taking a health action such as searching out health information online. An individual is more likely to perceive greater risks of psychological discomfort, time loss and poor quality information when they are using online health services when they believe themselves more vulnerable to a condition. Therefore:

H6b: Perceived susceptibility has a positive effect on perceived risk barriers.

Based on Gefen et al. (2003), we define trust as the consumer's belief in the integrity, benevolence, ability and predictability of the online health information provider. Trust is important to adoption because uncertainties characterize the use of e-services, which have resulted in consumers' trust beliefs being considered amongst the most important psychological states influencing online behaviors (Pavlou and Gefen 2002; Pavlou 2003; Kim et al. 2008). A trusted e-service provider is more likely to be perceived as offering accurate and useful information that is in the best interests of the consumer. Pavlou (2003) argues that trust reduces uncertainty and provides expectation for a satisfactory transaction experience. Trust is therefore considered important to consumer intentions to engage in the use of online health services (Song and Zahedi 2007; Yi et al. 2013). Therefore, we hypothesize:

H7a: Trust has a positive effect on consumer behavioral intentions toward online health information services.

The extended valence framework suggests that consumers are likely to perceive the potential for benefits only if the online provider is trusted to fulfill its obligations (Kim et al. 2009). If consumers trust an online health service as a reliable and competent provider of health information, they are more likely to believe the service will improve their effectiveness in managing their health. Past empirical study in the health context found that trust beliefs positively influence perceived benefits such as convenience (e.g., Lanseng and Andreassen 2007). Hence, we hypothesize:

H7b: Trust beliefs have a positive effect on the perceived benefits of online health information.

Trust and risk are arguably closely related. According to the extended valence framework trust is antecedent to risk perceptions because trust reduces the uncertainties that give rise to risk perceptions. Under this perspective, risk mediates the effects of trust on consumer acceptance (Jarvenpaa et al. 2000; Pavlou 2003; Nicolaou and McKnight 2006; Kim et al. 2008, 2009). Therefore, we hypothesize:

H7c: Trust beliefs lower the perceived risks associated with using online health information.

Research Methodology

Study design and procedures

To test our hypotheses, we carried out a laboratory-based experimental scenarios research design in a large national university in South Africa. We selected this context because students represent an important portion of online consumers (Kim et al. 2008) and a primary population using the Internet for health services (Bansal et al. 2010; Yi et al. 2014). Moreover, young people often have difficulties accessing traditional health services, and the Internet can offer them a confidential and convenient way to access health services (Gray et al. 2005). Even though college students are generally believed to be healthy, they still often struggle with responsible sexual behavior, confront mental health issues, drug and alcohol abuse, smoking, and poor eating habits (Bansal et al. 2010; Kim et al. 2012; McKinley and Ruppel 2014). In South Africa where this study was carried out, HIV/Aids represents a significant health issue facing the student population. One study suggests there was 3.4% at risk for HIV prevalence (HEAIDS, 2010). Moreover, other studies in the South Africa context have recorded that from age 18 to 34 years old, 11.1% have alcohol abuse disorders, and 4.6% population have drug abuse and mental health e.g., anxiety and depressive disorders (Herman et al. 2009). There are other issues associated with a large International student body including e.g. requirements for immunizations. Consequently, this student body selected for this study represents a diverse cross-section of the consumer population who confront various health-related issues. Many of these students are also learning to function independently at college without the typical family and support structures that surrounded them in their earlier childhood. The engagement of such consumer with online health information services is thus particularly useful to examine.

Our research design involved a first phase where participants were provided an opportunity to gain experience in the use of an online health service by completing a number of tasks. This was followed by a second phase for completing the survey questionnaire. We invited first year undergraduate students who are registered in computer-lab related courses to take part in the study. There are total around 1300 fist year students registered for the courses. In the first phase, we introduced the purpose of this study and identified three popular online health service websites to provide context for the experimental tasks (one leading local health information site and two international sites that have been used in other studies e.g. Zhang 2014). The websites were all general medical, health and wellness sites accessible to consumers with optional registration. The participants were asked to choose one of the three websites. Self-selection allowing participants the opportunity to select their own health information website increased the voluntary nature of the e-service usage process (Zahedi and Song 2008). Participants were asked to browse their chosen health website for information on a variety of issues in a number of general health categories that included diet and nutrition, exercise and fitness, and were asked to complete specific tasks related to the search for health information (see Appendix A). The tasks were adopted and redesigned from van Deursen (2012) and Keselman et al. (2008). The use of tasks aims to provide participants with some experience and exposure to their chosen health information website and promote variability in the use and attitudes toward using the site for maintaining and self-managing their health. Thus healthy students interested in health maintenance as well as student managing a specific health conditions constitute the study's population. The scenarios required approximately 25 minutes to complete. After that, in the second phase, participants were asked to complete an online questionnaire. The questionnaire captured the participants' perceptions on all the study's constructs. Demographic questions (e.g., age, gender and health information website experience) were also asked. The questionnaire was pre and pilot-tested prior to its administration. The relevant ethical clearances were received prior to data collection. To facilitate collection of responses, the questionnaire was distributed via the university's e-learning system. In order to increase the response rate, participants were given a small token of appreciation for their participation.

Measures

Constructs were operationalized based on previously validated instruments. Behavior intention (BI) was measured using scales developed by Bhattacherjee and Premkumar (2004). Given the online context, self-efficacy (SE) was measured using four items reflecting Internet self-efficacy adopted from Hsu and Chiu (2004). Perceived performance risk (RPE) was measured using the scale by Corbitt et al. (2003), Lee (2009) and Sun (2014). Perceived psychological risk (RPS) was measured using scales developed by Liao et al. (2009). Perceived time risk (RT) was measured by adapting scales developed by Featherman and Pavlou (2003) and Forsthe et al. (2006). In addition, three items developed by Ng et al. (2009) were used for measuring perceived severity (PSE). Three items developed by Goonawardene et al. (2013) were used to measure perceived susceptibility (PSU). Perceived benefit (PB) was measured by adapting the perceived usefulness scale developed by Bhattacherjee and Premkumar (2004). Three dimensions of trust (benevolence, ability and integrity) were measured using scales developed by Hwang and Lee (2012) and Thatcher et al. (2012). Demographic questions collected data on age and gender. Respondents were asked if they had used online health services before.

All items measured using a seven-point Likert-scale with anchors from "strongly disagree" to "strongly agree". Example measurement items for each construct are presented in the Table 1 below.

Constructs	Operationalization	Example Items
Behavior intention (BI)	3-item scale modified based on Bhattacherjee and Premkumar 2004.	I intend to continue using this website to obtain health information.
Self-efficacy (SE)	4-item scale modified based on Hsu and Chiu 2004.	I feel confident exchanging messages with others users in online discussion.
Perceived performance risk (RPE)	4-item scale modified based on Corbitt et al. 2003; Lee 2009; Sun 2014.	The health information site is risky, because it may not get what I want.
Perceived psychological risk (RPS)	3-item scale modified based on Liao et al. 2010.	The thought of using the health information site makes me feel psychologically uncomfortable.
Perceived time risk (RT)	2-item scale modified based on Featherman and Pavlou 2003; Forsythe et al. 2006.	Using the website may waste my time.
Perceived severity (PSE)	3-item scale modified based on Ng et al. 2009.	Not having access to health information is a serious problem for me.
Perceived susceptibility (PSU)	3-item scale modified based on Goonawardene et al. 2013.	My general health is in bad condition.
Perceived benefit (PB)	4-item scale modified based on Bhattacherjee and Premkumar 2004.	Using this website can be of benefit to me in managing my health.
Trust-Benevolence (TRB)	3-item scale modified based on Hwang and Lee 2012.	I expect this website information provider has good intentions toward me.
Trust-Ability (TRA)	4-item scale modified based on Thatcher et al. 2012.	I believe this website information provider is effective in assisting and fulfilling my searching.
Trust-Integrity (TRI)	4-item scale modified based on Thatcher et al. 2012.	This website information provider is truthful in its dealings with me.

Table 1. Questionnaire Items

Empirical Results

Participants

In total, 761 respondents completed our online scenarios and questionnaire. However, 58 responses were subsequently eliminated as they were missing a large number of data values or exhibited clear response patterns. Following the approach of Ragu-Nathan et al. (2008), the remaining sample (N=703) was randomly split into two sets. Set 1 (350 cases) was used for scale refinement through principal components analysis. Set 2 (353 cases) was used as a holdout sample for partial least squares analysis of the measurement model and structural model. Because participants were allowed to choose between three online health information providers for the carrying out the tasks and gaining familiarity with the online health service context, we did an ANOVA test to determine if trust, perceived barriers, self-efficacy, health beliefs, and the intention scores were independent of the choice of provider. Results indicated that there were no significant differences along the items measuring trust, perceived barriers, self-efficacy, health belief variables or intention variables.

Table 2 reports demographic profile of the 703 useable responses. The results show that 46.5% of the respondents were male and 53.5% were female. Among them, 52.1% respondents have had online health information seeking experience. Most of the participants chose website 1 and website 2 to do the scenario tasks, only a few participants chose website3. An ANOVA test showed that there were no significant differences across the three website choices. The largest age group consisted of those aged 18-19 (85.1%). Moreover, most of the participants had a smartphone (84.6%), and 76.2% participants have more than 4 years computer experience.

Demo-graphics	Category	n	%
Gender	Male	327	46.5
	Female	376	53.5
Age	18-19	598	85.1
	20-22	83	11.8
	23-25	9	1.3
	>25	13	1.8

Demo-graphics	Category	n	%
Online health information experience	Yes	366	52.1
	No	337	47.9
Choice of online health information service provider	Website 1	286	40.7
	Website 2	389	55.3
	Website 3	27	3.8
	Missing	1	0.1

Table 2. Descriptive Statistics of Respondents' Characteristics (N=703).

Common method bias

We checked for common method bias by performing Harman's one factor test (Podsakoff and Organ 1986). According to this approach, common method variance is present if one factor accounts for the majority of the covariance in the dependent and independent variables. An exploratory factor analysis (EFA) of all of our scale items revealed factors explaining 68.3% (N=703) of the variance in our study's constructs, the first factor explaining 24.8%, and the last factor explaining 3.5% of the total variance. These results suggest that no single factor explained a majority of the variance, thus supporting that common method bias was not a threat for this study.

We collected an additional 41 responses from students not registered in our surveyed classes who were present at different times of the day in other computer laboratories across campus. We compared their responses to those from our sample (N=703). No significant differences in responses was found, except for two items which given the number of items included in the instrument is likely due to chance. Thus we do not expect that the timing of our surveys, or the laboratory conditions or locations had an influence on our results.

Scale refinement

An initial principal components (PCA) analysis was carried out to confirm the unidimensionality of the measures and to eliminate any inappropriate items (N=350). We removed ISE3 at this stage. Thereafter, we carried out a separate PCA on the hold out sample (N=353) and the total sample (N=703) to determine if the same factor structures are reproduced. The results indicated that both holdout sample and total sample produced identical factor structures with ISE3 eliminate, and all items loaded on their expected theoretical constructs.

Measurement model assessment

We further assessed reliability and validity for each measure using Smart-PLS software package (version 2.0 M3) (Ringle et al. 2005). We tested two measurement and structural models, one each using the holdout sample (dataset 2: N=353), and one each using the whole dataset (N=703). We tested the measurement model with respect to internal consistency and discriminant validity. Table 3 reports item loadings, average variance extracted (AVE), composite reliability (CR) and alpha value for the measures. Item loadings are all above 0.70. Moreover, none of the items exhibited high cross-loadings on factors they were not intended to measure. Our AVE results ranged from 0.702 to 0.946 (full dataset) and 0.704 to 0.942 (holdout sample), which are above the recommended threshold value 0.5. Moreover, for scale reliability, all of the composite reliability (CR) values are above 0.875 and alpha values are above 0.734, which are above the acceptable values. Thus, the convergent validity is confirmed. We verified the discriminant validity of the constructs by checking the square root of the AVE. As shown in Table 4, the square root of AVE of each construct is larger than the inter-construct correlations, thus discriminant validity is confirmed.

	Items	Standardized Loading (353 vs. 703)		AVE (353 vs. 703)		CR (353 vs. 703)		Alpha Value (353 vs. 703)	
BI	BI1	.968	.971	.942	.946	.980	.981	.969	.971
	BI2	.974	.977						
	BI3	.970	.970						
ISE	ISE1	.885	.872	.704	.702	.877	.876	.790	.785
	ISE2	.868	.875						
	ISE4	.793	.762						
RPE	RPE1	.842	.839	.704	.705	.905	.905	.861	.861
	RPE2	.879	.869						
	RPE3	.832	.842						
	RPE4	.802	.807						
RPS	RPS1	.951	.925	.816	.825	.930	.934	.896	.896
	RPS2	.904	.920						
	RPS3	.853	.880						
RT	RT1	.807	.817	.780	.779	.875	.875	.742	.734
	RT2	.953	.943						
PSE	PSE1	.914	.908	.814	.808	.929	.926	.885	.881
	PSE2	.929	.921						
	PSE3	.903	.913						
PSU	PSU1	.896	.906	.817	.836	.931	.939	.889	.902
	PSU2	.913	.924						
	PSU3	.903	.913						
PB	PB1	.897	.905	.791	.815	.938	.946	.912	.924
	PB2	.913	.924						
	PB3	.868	.892						
	PB4	.880	.889						
TRB	TRA1	.916	.935	.841	.876	.941	.955	.905	.929
	TRA2	.938	.948						
	TRA3	.896	.926						
TRA	TRB1	.875	.883	.796	.825	.940	.950	.915	.929
	TRB2	.901	.919						
	TRB3	.899	.922						
	TRB4	.893	.909						
TRI	TRI1	.862	.880	.766	.804	.929	.943	.898	.919
	TRI2	.919	.918						
	TRI3	.870	.906						
	TRI4	.848	.882						

Table 3. Results of Reliability, Validity of the Construct Items

	Mean (S.D.)	BI	ISE	RPE	RPS	RT	PSE	PSU	PB	TRA	TRB	TRI
BI	4.88 (1.56)	**.971**										
SE	3.95 (1.58)	.139	**.839**									
RPE	3.87 (1.43)	-.297	-.016	**.839**								
RPS	3.00 (1.57)	-.101	.032	.434	**.903**							
RT	3.59 (1.56)	-.353	-.047	.554	.363	**.883**						
PSE	4.10 (1.75)	.385	.108	-.064	.020	-.085	**.902**					
PSU	3.15 (1.71)	.217	.037	.113	.258	.105	.340	**.904**				
PB	5.67 (1.10)	.344	.116	-.208	-.152	-.278	.115	.036	**.890**			
TRA	5.50 (1.03)	.576	.112	-.283	-.148	-.348	.256	.032	.401	**.892**		
TRB	5.60 (1.07)	.459	.071	-.246	-.157	-.264	.187	-.043	.276	.714	**.917**	
TRI	5.37 (1.01)	.505	.123	-.333	-.182	-.340	.215	-.021	.309	.785	.753	**.875**

Table 4. Construct Correlations (Diagonal bold values are square root of AVE N=353)

Notes: BI=Behavior intention; SE=Self-efficacy; RPE=Perceived performance risk; RPS=Perceived psychological risk; RT=Perceived time risk; PSE=Perceived severity; PSU=Perceived susceptibility; PB=Perceived benefit; TRA=Trust-Ability; TRB=Trust-Benevolence; TRI=Trust-Integrity.

Structural model assessment and hypothesis testing

After validating the measurement model, the hypotheses were tested by assessing the structural model in PLS. PLS is a variance based approach to modeling causal relationships among variables (Urbach and Ahlemann 2010). PLS provides a good approximation of alternative covariance-based approaches to structural equation modeling in terms of final estimates (Gefen et al. 2011; Hair et al. 2011; Sun et al. 2013). Bootstrap method (1000 re-samples) was used to determine the significance of the paths within the structural model. "Bootstrapping is a nonparametric approach for estimating precision which creates N samples to obtain N sets of parameter estimates" (Bliemel and Hassanein 2007). We controlled for the effects of age, gender, online heath information service experience, computer experience and smart phone ownership. This is because previous study suggests that demographic characteristic may influence online health service adoption behavior (Ybarra and Suman 2008). However, in our study, none of the control variables had the significant effect on behavior intention. Our model explains 47.5% of the variance of intentions to use the online health information services. We also tested our model by using the full dataset (N=703). The full data indicated that the R^2 value for consumer intention in online health information is 0.44, which means the model explains 44% of variance. The standardized path coefficients (β) results (N=353) of model testing are depicted in Figure 4.

As seen in Figure 4, perceived susceptibility had a significant positive effect on intention (β=.160, t=3.941), thus H1 was supported. Perceived severity had a significant positive effect on intention (β=.173, t=3.736), supporting H2. Perceived barrier as a higher-order factor had a significant negative effect on intention (β=-.160, t=3.743), thus H3 was supported. Perceived benefit had a significant positive effect on intention (β=.107, t=2.225), hence, H4 was supported. However, self-efficacy has no significant effect on consumer intention (β=.046, t=1.078). Therefore, H5a was rejected. The moderation effect indicates that self-efficacy moderates the effects of perceived severity on behavior intention (β=-.121, t=2.612), although perceived susceptibility's effect was not moderated by self-efficacy (β=-.004, t=.062). Thereby, H5c was supported and H5b was rejected. Perceived susceptibility had a significant positive on perceived severity (β=.342, t=7.237) and perceived barriers (β=.172, t=2.894), thus supporting H6a and H6B. Trust as a higher-order factor had a significant positive effect on intention (β=.462, t=9.467) and on perceived benefits (β=.365, t=6.118), as well as a significant negative effect on perceived barriers (β=-.368, t=8.221). Hence, H7a, H7b, and H7c were supported. Table 5 summarizes the results of this study.

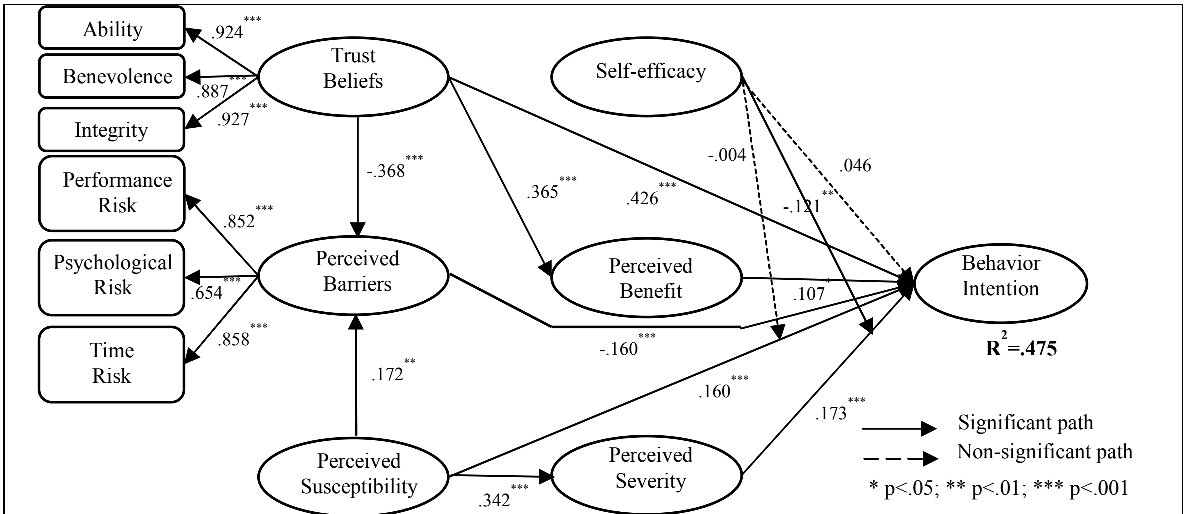

Figure 4. PLS Test of Research Model (N=353; * p<.05; ** p<.01; *** p<.001)

N=353			
Hypothesis (path)	Path coefficient	t-Value	Supported
H1	.160	3.941***	Yes
H2	.173	3.736***	Yes
H3	-.160	3.743***	Yes
H4	.107	2.225*	Yes
H5a	.046	1.078	No
H5b	-.004	.062	No
H5c	-.121	2.612**	Yes
H6a	.342	7.237***	Yes
H6b	.172	2.894**	Yes
H7a	.462	9.467***	Yes
H7b	.365	6.118***	Yes
H7c	-.368	8.221***	Yes

N=703			
Hypothesis (path)	Path coefficient	t-Value	Supported
H1	.132	4.034***	Yes
H2	.188	5.692***	Yes
H3	-.175	5.884***	Yes
H4	.154	4.564***	Yes
H5a	.060	1.83	No
H5b	-.01	.191	No
H5c	-.085	2.481*	Yes
H6a	.359	10.254***	Yes
H6b	.124	2.871**	Yes
H7a	.387	11.132***	Yes
H7b	.340	8.465***	Yes
H7c	-.357	10.278***	Yes

Table 5. Summary of Results (* p<.05; ** p<.01; *** p<.001)

Discussion

This study aimed to examine the factors influencing individuals' use of online health information services. To do so, we integrated the HBM and extended valence framework and empirically tested our research model. Data was collected in a laboratory setting from a sample of university students. Our study results in several important findings.

First, both perceived susceptibility and perceived severity had a significant positive impact on consumer acceptance of online health information services. The results show that the use of online health information services is a health-related behavior and that, consistent with the HBM, health threats are important to this behavior.

Second, outcome expectancies (perceived benefit and perceived barriers) do have a significant impact on behavioral intention. Perceived benefit positively influences intention, while perceived barriers negatively impact intention. This finding is consistent with theory of HBM and extended valence framework. It makes sense that the more barrier perceptions the less positive behavioral intentions. The results suggest that online health information service providers should minimize barrier perceptions and maximize perceived benefits to promote positive intentions towards using online health information. This implies that consumers value information that will help them improve their performance in managing their health. Importantly, performance risk, psychological risk and time risk represent three barriers. Online health information providers should understand the multi-dimensional nature of risk and that performance, psychological and time losses are important barriers to consumers.

Third, it is worth noting that self-efficacy had a non-significant impact on consumer intentions. This is not consistent with HBM although a non-significant relationship between self-efficacy and intention has been found in other health behavioral studies (e.g., Wong and Tang 2005). This can be explained by the possibility that younger online consumers (who constituted our study sample) may possess greater Internet self-efficacy (which was examined in our model), thereby making this factors less relevant to their acceptance of online health services than might be the case in a broader consumer sample (McKinley and Ruppel 2014).

Self-efficacy was found to negatively moderate the effect of perceived severity on behavioral intention toward online health information services. Thus when individuals have low self-efficacy, perceived severity is more important to their behavioral intentions. Thus for individuals with lower self-efficacy, it is only when confronted by serious clinical or social consequences of a health condition are they able to overcome lower self-efficacy to engage in the use of the online service. This is however contradictory to our expectation that individual with lower self-efficacy may perceive less value in the use of online health sites to act against prevention health threats. However, our findings are consistent with McKinley and Ruppel's (2014) discussion regarding the nature of self-efficacy's moderating effects on online health behavior. We did not however find self-efficacy to moderate the relationship between perceived susceptibility and behavioral intention. This result is inconsistent with Carpenter's (2010) suggestion. Perceived susceptibility did however have a significant direct effect on perceived barriers. Moreover, participants who believe themselves more vulnerable to a health threat are more likely to be concerned with the risks associated with using the online service. Severity was also shown to partially intervene in the effects of susceptibility. The serious of the health condition and not just vulnerability to the condition is important to behavior.

Fifth, we found that trust had the strongest direct impact on behavioral intention. This finding supports the view that trust is important to consumer acceptance of online health services. Thus the use of online health services is driven by typical e-service concerns for trust in the ability, benevolence and integrity of the online provider. This is a particularly useful finding for the service providers. In addition, consumer trust has a strongly significant negative effect on perceived barriers. This supports the arguments that trust lowers risks as barriers to consumer acceptance of e-services (e.g., Pavlou 2003; Gefen et al. 2003). Perceived benefit was influenced by trust beliefs. This result indicated that consumers only believe they will gain benefits from a trusted health information provider. The findings are consistent with the extended valence framework.

Implications and Conclusion

Implications for theory

Form a theoretical perspective, our study has the following theoretical contributions. First, this study attempts to extend valence framework to non-commercial service context. More specifically, we empirically validated this theoretical framework into online health information service area. Previous applications have focused on e-commerce or mobile commerce (e.g., Kim et al. 2009; Lu et al. 2011; Lin et al. 2014). To the best of our knowledge, there are no studies adopting the extended valence framework to study online health behaviors.

Second, unlike many of previous studies of HBM that examine general health behaviors (e.g., Marlow et al. 2009; Kim et al. 2012), we have shown it relevant also to the study of online health information seeking and extended recent work (McKinley and Ruppel 2014).

Our results indicate that health beliefs and the valence framework are two fundamental aspects that health information seekers take into account when making their decisions about online health services. To our best knowledge, no other study has integrated HBM and extended valence framework to study online heath behaviors.

Third, the results of this study highlight the role of trust and barriers in consumer acceptance of online health information service context. More specifically, we identified the multifaceted barriers include performance risk, psychological risk and time risk. While, trust beliefs include online service provider's ability, benevolence and integrity. Moreover, we show that trust is not only salient in commercial e-service contexts but also extends to in the non-commercial online health services context. Our finding of trust and barriers can be reliably modeled as a higher-order construct. This can help future researchers to more comprehensively capture these constructs in the e-service context.

Implications for practice

This study also has several important practical implications. First, our study indicated that trust have the strongest directly effects on behavioral intentions. The importance of three dimensions of trust in this study namely, online health services providers' ability, benevolence, and integrity can help practitioners better understand the formation of trust. Practitioners need to ensure that they increase provider-based trust by building their reputation as a reliable, competent provider of health information and that they are seen to do so in a manner that is in the best interests of consumers rather than, for example, pharmaceutical companies or commercial advertisers on their sites.

Second, the salient and negative effect of perceived barriers on intention implies that barriers play an important role in dampening consumers' online health information acceptance behavior. By modeling perceived barriers as performance risk, psychological risk and time risk that negatively affect online health information acceptance. This suggests that when online health service providers promote their health information to facilitate the potential online health information seekers, they should countermeasures those barriers. For example, online health information service provider may reduce performance risk by providing evidence of sources used to compile the health information, mitigate time loss by providing a friendly interface, good search navigation and clear categories to index information, and through the provision of simple and actionable information may help break the psychological anxieties associated with site use.

Third, perceived benefits, perceived susceptibility and perceived severity are other important factors influencing consumer behaviors. Individuals are more likely to seek out health information when they perceive their general health as poorer and have a need for access to health information. This finding can help service providers to understand the profiles of consumers that may come to interact with their sites and how perceived health threats as well as the need for improved self-management are important to their motivation. Health sites should empower self-management in a manner that allows for better decision making based on differing levels of susceptibility and severity e.g. through advanced search options.

Limitations and future research

It is important to note some limitations of our study. First, the sample is drawn from a university population and this is a recognized threat to the generalizability of the conclusions to broader consumer populations, future research may wish replace our study using other samples such as: adults with chronic diseases. Second, some of the tasks may not be applicable to all consumers and may have created bias in their perceptions (Lanseng and Andreassen 2007). Third, our data was also cross-sectional and therefore causal inferences can only be made with reference to theory. Future studies may wish to adopt longitudinal designs and consider the temporal changes in extended valence framework as well as health belief behavior towards online health services. Because this study has confirmed trust as multi-dimensional and as highly important to acceptance, future research may wish to determine the specific antecedents that can influence trust in digital health innovations and may wish to consider other variables potentially unique to the healthcare context such as emotion (Anderson and Agarwal 2011). Moreover, future research may wish to conduct a longitudinal study to consider whether trust belief and health beliefs change over time. For example, some researchers have argued that earlier beliefs may influence later beliefs in consumer acceptance of new technology (e.g., Bhattacherjee and Premkumar 2004; Venkatesh et al. 2011; Hsu et al. 2006).

Conclusion

This study develops a research model to understand consumer acceptance of online health information services by integrating health belief model (HBM) and extended valence framework. We used a laboratory-based experimental scenarios research design to collect data from a sample of 703 university students in South Africa. To test our hypotheses, trust and perceived risk barriers were modeled as higher-order constructs. Our multi-dimensional trust construct was found to have the strongest effect on consumer acceptance. Perceived risk barriers were also found to have a direct significant negative effect on consumer acceptance. Furthermore, we confirmed health belief variables such as perceived susceptibility and severity are important to consumer acceptance of online health information services and perceived susceptibility has a significant positive effect on perceived severity. Self-efficacy had non-significant effects on intentions; however, it was found to moderate the effect of perceived severity on consumer behavioral intentions. The model explains 47.5% of the variance of intentions to use the online health information services. Results have helped us identify the relative salience of HBM and extended valence framework in consumer acceptance of online health information services and have important implications for practice.

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Appendix A: Task Sheet

Please visit one of the following websites:

Website 1: [xxx]; Website 2: [xxx]; Website 3: [xxx]

1. Which website did you visit?

Please complete the following tasks using your chosen website.

2. Identify a health related topic of interest to you. Then using your chosen website's search feature search for information on this topic: How relevant to you did you find the articles?

A. Not at all relevant. B. Somewhat relevant. C. Relevant. D. Very relevant.

3. Read one of the articles, and answer the following questions:

What is its title?

When was it written?

4. What information is required to register or sign up to your chosen website?

5. Does this website contain information on second-hand smoke?

(1). Yes (2). No

6. Imagine… You are visiting your elderly relative who lives alone, in another part of the country. On the second day of your visit, she carries several bags of groceries up two flights of stairs and stops with a pained expression on her face. When you press her to tell you what is wrong, she admits that she is having chest pain. She says that the pain feels as if something were squeezing her chest. She is also nauseous and out of breath. She lies down to rest. The discomfort lasts 2–3 minutes, after which the pain stops.

When you talk to her about this incident, she admits that for the past year, she has been troubled by periodic squeezing pain in her chest. Sometimes she can also feel the pain in her neck and shoulders. The pain usually happens after she does something physically active: climbs several flights of stairs, does some heavy housework, unloads groceries, etc. When this happens, she also often feels nauseous and out of breath. She also feels very tired. The pain typically lasts a few minutes and goes away after she rests a while.

Using your chosen website, try to identify what is the name of the condition your elderly relative suffers from?

7. Imagine… During a hike you are bitten by a tick. A red spot appears that increases. This is a sign you have been infected with Lyme borreliosis. A friend recommends starting with an antiviral (remedy against viral infections) immediately, since Lyme's disease can have very unpleasant consequences, especially when treatment starts too late! Answer the following question using your chosen website:

Does this website provide any information to help you make a decision as to whether or not it is a good idea to start an antiviral remedy?

A. Yes. B. No. C. No information.

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